Supplementary Table S1: Comparison of reported machine learning models for prediction of iron deficiency anemia(IDA)

Paper	Target	Features	Data	Subject Age group	Model with highest performance	Reported performance metrics	Observations
Bellinger, Amid, Japkowicz, & Victor, 2015	Predict IDA, β-thalassemia and IDA+β-thalassemia	sex, age, Hb, Hct, RBC, RDW	562 anemic instances 59.3% IDA, 23.3% to β-thalassemia and 17.4% IDA+β-thal	Pediatric population	MLP	Precision:0.7278 Recall:0.8308 F1score: 0.7212 ROC-AUC 0.9102	-
Ayyıldız & Tuncer, 2020	Differential diagnosis of IDA and β-thalassemia	Gender, RBC, Hb , HCT , MCV ,MCH, MCHC and RDW	152 patients diagnosed with β-thalassemia and 190 diagnosed with IDA	1-88 years	Neighborhood Component Analysis	Accuracy: 0.953 Precision:0.952 Recall: 0.962 F1 score:0.957 ROC AUC:0.97	-
Saputra, Sunat, & Ratnaningsih, 2023	Differential diagnosis of B-thalassemia, IDA and hemoglobin E or combination of IDA with other	RBC, Hb, HCT, RDW, MCV, MCH, MCHC	190, 24 with BTT, 41 with Hb-E, 104 with IDA and 21 with combinations	15-41 years	Extreme Learning Machine	Metrics for IDA classification Accurasy:98.44 Precision: 100 Recall:93.75 F1 score:96.77	-
Yıldız, Yurtay, & Öneç, 2021	12 different types of anemia including IDA	Age, sex, CBC data, ferritin, serum iron parameters, vitamin B12, bilirubin.	1663	20-109 years	Boosted trees	Accurasy:83.2 Precision: 96.7 Recall:78.1 F1 score:0.864 ROC AUC:0.98	Ferritin and serum iron included in both the train and test data set
Dogan & Turkoglu, 2008	IDA and Non IDA	Serum iron, total iron binding capacity and serum ferritin	96	Not given	Decision support system	100% sensitivity and specificity	Serum iron parameters and ferritin are included in classification. No CBC data involved.
Yilmaz, Dagli, & Allahverdi, 2013	IDA and Non IDA	Hb, MCV, serum iron, total binding capacity (TIBC), and serum ferritin	100	Not given	Rule based classification based on specific reference values	The success level of the system was detected between 90% and 95.8% with different parameters	Serum iron parameters and Ferritin included in rule-based classification

Azarkhish, Raoufy, & Gharibzadeh, 2012	IDA or No IDA	MCV, MCH, MCHC, Hb/RBC	203 (92 males; 111 females)	55.8± 17.78	Artificial Neural Network	Accurasy:96.29 Recall: 96.8 Specificity: 95.6	Classification of ID is based on serum iron, and not ferritin which is gold standard suggested method by WHO.
Terzi et al., 2022	IDA and Non IDA	Age, Ferritin, iron, Hb, HCT, MCV, RDW, RBC, MCHC,	516	17-89	XG boost	Accuracy:0.98 Recall:0.99 ROC AUC: 0.99	Ferritin used as feature in both train and test datasets
Kurstjens et al., 2022	Prediction of low serum ferritin or IDA	Age, sex, CBC data and CRP	8021 Anemic adult subjects	More than 18 years age	Random Forest	Specificity:92 Sensititivity:98 ROC AUC: 0.90	The model was developed with data of only adult anemic subjects, and in a hospital setting. Additional CRP variable is included in the features along with CBC.
Proposed Model	IDA or No IDA	Age, gender, pregnancy status, CBC data	19995 subjects	1-60 years	Gradient Boost	Accurasy:0.97 Precision: 0.63 Recall: 0.98 ROC AUC: 0.99 PR AUC:0.86	Survey data from general population, includes all age groups (1-60 years) including pregnant women.

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